TOWARD A THEORY OF MESO-SCALE WILDFIRE MODELING - A COMPLEX SYSTEMS APPROACH USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

Wildfire occurs over a wide range of spatial and temporal scales. Typically, patterns of wildfire spread are modeled using fine-scale, mechanistic equations or broad-scale, probabilistic equations. Both modeling approaches use some form of fuel, climate, and topography variables. Mechanistic approaches look at the small scale constraints (e.g., percent of moisture in fuel) that enable a fire to keep burning. In probabilistic models fire spread is determined by the size and connectedness of fuel patches distributed across the fire landscape. Both approaches assume the fire behavior environment is a simple system that can be described with simple equations, but that assumption holds true only over a very narrow range of scales. A complex systems approach to modeling fire behavior involves not only knowing what variables are constraining fire growth at a fine scale but also which constraints are absent at a broad-scale, allowing a fire to spread unchecked. Possession of highly detailedinformation on system variables will not inform you where the system is going because small changes in the context will change the importance of certain variables. What is important are the cross-scale relationships between the upper-level context and lower-level constraints to the predictor variables of the model. Existing fire models lose predictive power when subtle shifts in environmental variables cause qualitative changes in fire behavior, that is, when the system's behavior changes scale. Artificial neural networks (ANNs) are designed for problems with cross-scale relationships that produce non-linear changes in system behavior. The ANN framework provides a comprehensive integration across scales of fire environment variables. The ANN is able to determine the equations describing those cross-scale interactions and better predict where a fire will spread as a result. This better predictive capacity is needed in light of global climate change and increasing human habitation in rural areas.

INTRODUCTION

The need for a meso-scale wildfire model stems from a Forest Service initiative to assess and analyze fire-regulated ecosystems in the northern Great Lakes States. Forest Service research activities in the Lake States have included fire occurrence factor analyses (Cardille 1998) and disturbance regime mapping for certain subsections within Province 212 (Keys, et al. 1995). A useful fire model should be appropriate for use on National Forests and surrounding lands within the Province and facilitate the development of alternative strategies for ecosystem management. Linking the model to a forest succession model will aid in planning and evaluating burning as a land management practice.

We model fire to better manage fire and its effects on ecosystems, communities and landscapes. Some fire models are stand-alone while others are modules within larger land cover dynamics models. Extant fire models operate at many scales, use different predictive equations, and produce numbers or maps representing fire frequency, severity, spread rate, burn pattern or risk. A meso-scale fire model is needed for several reasons. Many fire models were originally developed for the conifer-dominated forests of the western U. S. Ecosystem differences (e.g., wind/elevation interactions, landform and cover type characteristics, etc.) may make these model structures inappropriate for the Great Lakes ecoregion. Wildfire modules within larger forest succession models lack the resolution required for most forest-level management and planning efforts. Increasing human presence on and around forested lands in the region raises the potential for conflicting land management scenarios (Plevel 1997). Therefore, forest land managers recognize the need for a wildfire model specifically applicable to the northern Great Lakes ecoregion.

The unique aspect of this model is the use of an artificial neural network (ANN) as the decision-making engine. An ANN-based wildfire model is distinctive in comparison to contemporary models. Extant fire models have their strong points, but ANN models offer advantages for some data availability and field situations in two ways. First, they integrate relationships between fire environment variables (fuel, topography and climate) relating to fire behavior that occurs at multiple spatio-temporal scales. Second, they allow the capture and analysis of cover, landform and climate interactions that may be unique in time and space with respect to predicting fire spread.

The ANN model structure should be robust in predicting wildfire burn patterns over the range of fire environments present in the ecoregion. Traditional modeling approaches require that the rules relating input to output be known *a priori*. Accuracy of the predicted variables relies on the precision of the input variables, so a lack of data for one component module or equation will cause the whole model to fail. In contrast, ANN models need no explicit statement of the rules (they will be learned via inductive reasoning), are fault tolerant (due to redundancies within the network), and can function with noisy or partial data.

ARTIFICIAL NEURAL NETWORKS

Haykin (1994) defines a neural network as ". . . a massively parallel distributed processor that has a natural propensity for storing experiential knowledge and making it available for use." Artificial neural networks acquire knowledge by learning from examples and store that knowledge as synaptic weights in connections (networks) between processing nodes (neurons). ANNs have the ability to model complex functional relationships predefining the behavior and interactions of all the pertinent components (i.e., the rules are not known). The pattern emerges through positive feedbacks that eventually press against global constraints that define structure. ANNs reduce the need to write "rules" based on expert knowledge. Neural networks determine these rules by mapping directly from input to output with a blind, but effective, search strategy (Sui 1994). A trained network can respond non-linearly to input values, where a small change in one or several inputs can result in an exponentially greater output response. Conventional modeling techniques do not readily do this unless the relationships are known *a priori*. Since their inception, artificial neural networks have been trained to perform tasks that appeared impossible for conventional computer programming techniques, for example, steering a car under new or unknown conditions, reading hand-written postal zip codes, or recognizing spoken language (Dukelow 1994).

Basic ANN Architecture

Conceptually neural networks are quite simple and can be represented as graphs composed of a series of linked nodes (Figure 1) that represent biological neurons and their connections. Multi-layered, feed-forward networks are acyclic graphs and have a series of nodes arranged in layers (input, hidden and output), with links between every node in adjacent layers (Figure 2). Full connectivity is not a requirement for a functioning neural network. There are typically only one input and one output layer. A network with one hidden layer can learn most continuous functions, while multiple hidden layers can learn discontinuous functions (Russel and Norvig 1995). Each link in the network has a numeric weight, the strength (value) of which relates to the local node's effect on the whole network. Input values are multiplied by the weights of the input links leading to each node in the hidden layer (Figure 1). Each node in the hidden and output layers performs two functions: a linear summation of the weighted inputs and then a nonlinear transformation of that sum using an activation function (Russel and Norvig 1995). The activation function produces an activation value for each hidden node that is "fed forward" to the output layer. The nodes of the output layer also calculate a weighted sum, and the activation function produces the output value.

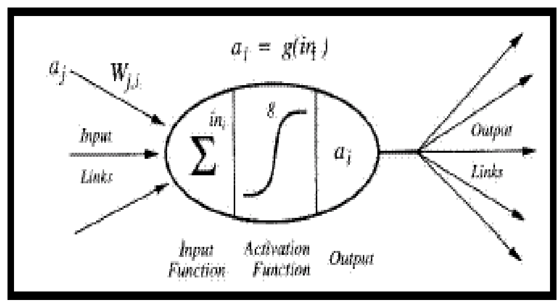

Figure 1. A neural network processing unit. (Adapted from Russel and Norvig 1995)

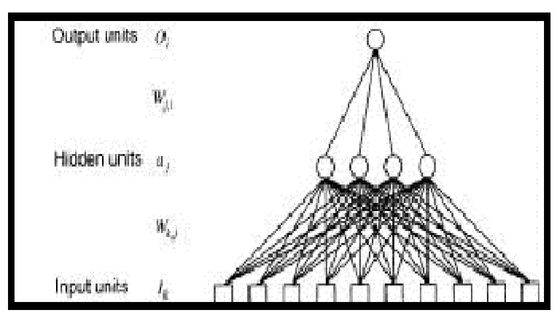

Figure 2. A single-hidden layer feed-forward artificial neural network. (Adapted from Russel and Norvig 1995)

QUALITATIVE ANALYSIS OF THE FIRE ENVIRONMENT

Wildfire occurs over a continuous spatio-temporal range (Simard 1991; Turner and Dale 1991). The elements of the fire environment triangle - fuel, weather and topography - also vary continuously over the range of scales that wildfire occurs. Approaches to modeling wildfire spread patterns are either fine-scale mechanistic or broad-scale probabilistic (McKenzie, Peterson and Alvarado 1996). While both approaches correlate observed fire behavior with fuel, climate, and topography variables, they only work within a narrow, fixed-scale range. Mechanistic approaches scale locally to what keeps a fire burning, while fire spread in probabilistic models is constrained by the rate of percolation across the landscape. To work within a meso-scale range, both approaches extrapolate model results up- or down-scale, or aggregate fire environment variables to the desired scale of analysis. Extrapolating up-scale from physically-based equations or down-scale from statistically-derived landscape variables results in less predictive power because the relationships between the fire environment variables change in a complex, non-linear manner as the scale shifts away from that of the original model. Changing spatial and temporal scales of fire environment variables leads to the inherent unpredictability found in middle number systems (Weinberg 1975; Allen and Starr 1982).

Small number considerations, like our planetary system, are predictive because one can account for the behavior of each component with one equation for each part. Large number systems, e.g., the gas laws, have so many parts ($N > 6.02x10^{23}$, Avogadro's number) that statistical techniques are employed to predict overall system behavior based on the assumed average component. Middle number systems lie between the domains of these two approaches; there are too many components to account for the behavior and interactions of all the parts, but too few to permit the assumption of uniform behavior. Middle number systems are extremely sensitive to initial conditions because any component or process may enter into feedback and come to dominate system behavior.

Fire literature has focused on either the constraints on fires raging or the constraints on fires surviving, but not both sets of constraints. Each class of model is predictive to a limited degree. What is needed, and what ANNs provide, is prediction in the context of both sets of constraints simultaneously. Switching constraints, however, means predicting within a middle number domain where one set of constraint factors is historical, and the other can be captured in a relatively mechanistic account. Since history and mechanism are not compatible, our meso-model cannot be purely mechanistic or probabilistic. In the middle number domain, fixed scale simulations or fine-scale, physically-based models lack sufficient flexibility and miss important dynamic interactions. Predictive modeling of fire behavior involves knowing what variables are constraining fire growth or which constraints are absent allowing unchecked positive feedback between fire and fuel. Extant fire models lose predictive power when subtle shifts in environmental variables cause a qualitative change in fire behavior.

Most modeling approaches select and theorize about environmental parameters based on observations and expert knowledge. Parameters are calibrated using reasonable assumptions and probabilities to incorporate processes that are well understood or easily encoded. Once calibrated, parameters are dealt with as constants in models. This fixes the scale over which the model is valid and limits the resolution. On average, working models behave as expected and give solid results when parameters do not exceed their normal range. Models often fail to predict larger events because those events lie beyond the averaged model parameter values and the process is initiated by a low probability, but ecologically possible, alignment of environmental conditions. Fixed-scale models are often inflexible, only valid within a narrow state space, and provide inadequate responses during conditions when the modeled system switches from being controlled from below by internal processes to being controlled from above by external constraints.

System Scaling

O'Neill, et al. (1986) show that hierarchy theory (Allen and Starr 1982), when applied to ecosystem processes and functions, can provide a useful approach to situations that appear middle-number. By empirically determining and hierarchically ordering the system rate variables, we limit the imposition of predetermined, human-based scales on our analyses. In discussing fire and insect effects on boreal forest ecosystems, Holling (1981) describes a simulation model that requires equations with 78 variables to predict adequately spruce budworm dynamics in only one forest patch. With 393 patches in the affected area, a comprehensive simulation model would contain more than 30,000 variables. Using a topological approach, the 78 local variables reduced to three rate sets relating to budworms (fast, months), foliage condition (intermediate, years), and crown volume/hectare (slow, decades).

While the topological approach is qualitative in nature, it is very instructive in understanding how and why system dynamics change with a change in variable values. Where the simulation model provides detailed, essentially mechanistic, explanations of what happens in the system, its complexity precludes understanding how and why results are produced. Holling (1981) presents a similar topological analysis of fire (Figure 3). Fire intensity is the fast variable, fuel intermediate, and trees slow. This simple model shows an equilibrium manifold (solid line) where the region to the left of the line represents conditions where self-sustaining fire is not possible. Along the curve and to the right, fuel conditions and fire intensities are sufficient to sustain combustion. The line at B represents the average intensity of random ignition events. Fuel conditions less than **A** do not allow sustained fire under any intensities. As fuel condition increases toward C, the regular, random ignitions would result in a self-sustaining fire whenever **C** was reached. Fire suppression or changing climate deflects the lower arm of the equilibrium manifold upward, preventing sustained combustion at lower fuel conditions (slow variables constraining fast). Over time tree crown cover increases, creating conditions capable of sustaining a crown fire, a significant change in state of the intermediate variable. Eventually a hot, dry year will occur, and while fast atmospherics still control the fast fire variables, previous slow variable constraints have set the stage for large scale conflagration (Figure 3, **E** to **F**). The manifold in Figure 3 assumes that tree density, the slow variable, is in some type of equilibrium; the manifold aids in understanding why a landscape experiences regular and periodic fires of moderate intensity (**D**) despite frequent, random ignitions.

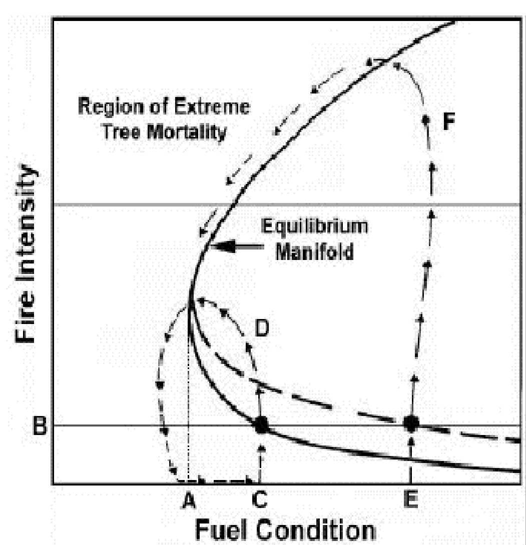

Figure 3. Fire environment manifold. (Adapted from Holling 1981)

Fire behavior always involves the question of what variables will be controlling, providing the constraints on fire, or which constraints are absent, allowing unchecked positive feedback between fire and fuel. Fixed-scale simulations or fine-scale, physically-based models lack sufficient flexibility and will miss important dynamic interactions. Management use of these models will result in surprise (Holling 1986). By ignoring spatial aspects and folding other temporal variables into only three, topological analyses offer an understanding of fire behavior at any spatial scale (e.g., needle, tree, stand, forest). Atmospheric variables can also be represented as fast (relative humidity, precipitation), intermediate (seasonal temperature and annual precipitation), or slow (climatic averages over decades or centuries) (Figure 4).

Fire models based on Rothermel's (1972) equations use fast atmospheric variables to predict fire intensity with fuel models that implicitly incorporate intermediate and slow climatic variables (Figure 4). Rothermel's analysis (Rothermel 1991) of model predictions during the 1988 Yellowstone fires shows how reliant the equations are on fast/fine scale information. Extant models appear to map between fire and landscape but only weakly to atmosphere, or between

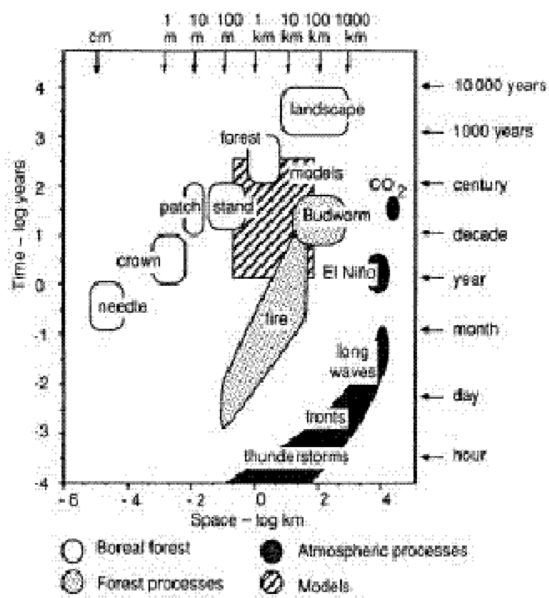

Figure 4. Time and space scales for the boreal forest and their relationship to some of the processes which structure the forest. Contagious meso-scale disturbance processes provide a linkage between macro-scale atmospheric processes and micro-scale landscape processes. (Adapted from Holling, et al. 1996)

fire and atmosphere but only weakly to landscape. These models make only simple connections between the elements in Figure 4 over a narrow scale range. An adaptive model would seek connections across multiple scales, creating pathways among all levels of slow-intermediate-fast and micro-meso-macro variables.

It is easy to extrapolate the manifold line (representing a compression of the other variables in a complex fire environment, Figure 3) to an n-dimensional space, and hypothesize that subtle shifts in several variables will shift the bottom of the manifold up or down, crossing B at different locations. This complex view of fire is well modeled with ANNs, since fast, intermediate and slow variables can be somewhat isolated within the network, having only minimal connectance to other portions of the network. The ANN framework provides a comprehensive integration across scales of biotic and abiotic variables. The actual equations describing those cross-scale interactions are contained in the weights of the network.

EXTANT FIRE MODELING APPROACHES

All fire models look at fire spread from the standpoint of the flames pushing the fire front along if fuels are available or wind is strong enough. Results from some fire spread models suggest that different upper-level elements are controlling under varied environmental conditions (Green, Tridgell and Gill 1990; Gardner, et al. 1996). Through repeated simulations these models can determine the degree to which a given landscape is connected (i.e., able to carry a fire), when it is above or below some critical threshold value (Green 1994; Turner, et al. 1989). Information on percolation thresholds is needed for fire management of present-day landscapes and should be incorporated into wildfire models. Indeed, Turner and Romme (1994) and others (Simard 1991; McKenzie, Peterson and Alvarado 1996) discuss the need for a link between fine-scale mechanistic and broad-scale probabilistic wildfire models. They point directly to the essential need to be able to determine when landscape pattern or fire-line thermodynamics provides the more important constraint on wildfire spread.

Wildfire models (e.g., Andrews 1986; Finney 1996; Gardner, et al. 1996; Clarke, Brass and Riggan 1994) operate by encoding endogenous fire processes (e.g., rate of spread, intensity, etc.). While each fire model has different, specific input requirements, any model of wildfire will require, in general, fuel, weather, and topography data (Fons 1946). What is usually neglected in mechanistic models of wildfire is the overlying landscape structure and variable climate that serves as context for and constraint on disturbance processes (Allen and Hoekstra 1992; Holling, et al. 1996; Simard 1991).

For simplicity ecosystem models usually only incorporate two hierarchical levels (Holling 1995). Incorporating fire regime into these model sets intermediate variables of fuel and weather as the lower-level context; the model then simulates effects on forests with variation in climate (both, higher-level, slower-acting variables). Alternatively, physically-based fire models encode low-level, fast combustion processes and scale-up to stands and forests. Local, human impacts on the biosphere are having global effects (e.g., rising CO_2 levels), crossing scales and ecological disciplines. Human society is now acting on a scale and at a rate equivalent with ecosystems, so our models must start to include variables from more than two hierarchical levels. The difficulty in modeling these effects has been in connecting processes operating at vastly different rates (Allen and Starr 1982). Encoding each process with its own time step would be cumbersome and lead to very complicated models. Even if the computer code could capture the details of a single process, the cross-scale interactions of different processes are not likely to be known or knowable.

Other Approaches to Modeling Fire

Other recently developed models have taken advantage of raster-based simulation concepts (e.g., cellular automata (CA) and nearest neighbor decision rules) to incorporate concepts of diffusion (Clarke, Brass and Riggan 1994), percolation (Green 1993b), or contagion (Li and Apps 1996; Gardner, et al. 1996) in spreading fire across a landscape. CA are a 2-dimensional array of cells with values that represent the global state of a variable. Each cell is a computer and updates its state at each time step based on the state of its neighbors (Green 1993a). Limiting interactions to immediate neighbors makes CAs easy to computerize, and the efficient processing is often used to model complex systems (Karafyllidis and Thanailakis 1997). Most CA models of fire spread require some estimate of the burn potential for each cell prior to running the model. The probabilities are often stochastic in nature, and multiple runs are used to develop a map of fire risk. Cellular automata have been implemented in fire models using Rothermel's (or others) rate of spread (Ball and Guertin 1992; Karafyllidis and Thanailakis 1997), Huygens' principle (French, Anderson and Catchpole

1990), nearest-neighbor movement rules (Bryant, et al. 1993; Ratz 1995) and invasive epidemic processes (Green, Tridgell and Gill 1990). Clarke et al. (1994) present a unique method of fire propagation in a CA.

Using only local rules means that the emergent pattern often represents what is physically possible, though not necessarily ecologically allowable (Allen and Hoekstra 1992). CA fire models often produce distorted or unnatural fire boundary shapes (French, Anderson and Catchpole 1990; Ball and Guertin 1992). By using only nearest neighbor rules, CA models do not incorporate a context, the ecological constraints that limit the total range of physically possible to a smaller subset of ecologically allowable structural and organizational configurations. The ANN model, while grid-based, makes local decisions but also incorporates information from the surrounding landscape to provide a context.

CONCEPTS OF ECOSYSTEM CHANGE

Humans, fire, wind, disease and insects are the major agents of change in forests. Fire is a perturbation at the scale of a tree, while at the scale of a forest, fire is an integral, endogenous ecosystem process (Allen and Starr 1982). While fire kills individual trees, it initiates a cycle of stand renewal, often ensuring the survival of the tree species. Fire operates over multiple spatio-temporal scales, and characteristics of the variables that control fire behavior also vary in time and space. Topography is relatively stable over time but exhibits great spatial variation. Fuel and climate vary in both time and space. Fuel is stored energy on the landscape (Sapsis and Martin 1993). Fuel state describes the moisture content of live and dead fuels. Change in fuel state can be rapid (daily) or intermediate (seasonal/annual). Fuel type refers to species, spatial arrangement (vertical and horizontal) and density. Fuel accumulation after a fire is generally a slow process that can continue for 100 years or more, although some disturbances (insect outbreaks, disease, windthrow) will cause more rapid fuel accumulation.

Fire alters the condition and arrangement of abiotic and biotic elements on a landscape, and species respond to the changed environment. The type of vegetation that returns after a fire determines in part when fire will return and how severe its effects will be. This positive feedback loop between species and fire can develop into a relatively stable system over time, assuming that large scale climate (the upper-level constraint) remains constant. With shifting climate, human impacts and exotic invaders, present day fire regimes cannot be readily discerned from historical data (Schoonmaker effects they want to produce with fire, and determine an appropriate fire regime to meet those expectations (Pahl-Wostl 1998). The scale of the underlying disturbance regime(s) and the physical space on the landscape required for disturbance processes to occur are important factors to consider when developing any meso-scale model of fire.

Rowe (1983) identified five life history mechanisms that plants use in response to different fire regimes. In areas that experience a range of fire severities, a species may employ several of these strategies to survive. Fire suppression favors avoiders and results in densely stocked, late successional forests. The key point is species are not the relevant entities with respect to fire regime, rather Rowe's strategy categories are. Fire interval will equilibrate through positive feedback with vegetation (ordered along Rowe's strategy categories) to maintain fire intensity and severity. Fire intensity is a fast, local variable (low level dynamics). The lag in the period over which fuel accumulates on the landscape (intermediate variable in space and time) acts to constrain intensity.

To achieve environmental constancy (i.e., an equilibrium) one is required to fix scale in space and time. By averaging variability in time and graininess in space, an emphasis is placed on nature as a constant over time. This leads to management policies that are unprepared for and surprised by change (Holling 1986). Figure 5d represents an equilibrium-centered view of the material world where the ball, i.e., environmental variables, always returns to a single stability point following disturbance (Holling, et al. 1995). A more dynamic view of change (Figure 5a) incorporates multiple stability points. Equilibrium views assume linear causation wherein a small change in an environmental variable causes only a small change in system state. Multiple stable equilibria indicate spatial and temporal variability and nonlinear causation. Planning and policy derived from an equilibrium basis will not recognize stable configurations beyond the one in which the system resides. Continual, constant environmental change displaces the ball short distances over time (Figure 5b), yet the system state appears to be within the same basin of attraction (linear change in environmental variables). Further small changes in the environment result in a sudden, nonlinear change in state, with the system moving to another stability point (Figure 5c), a surprise from the equilibrium viewpoint (Holling 1994).

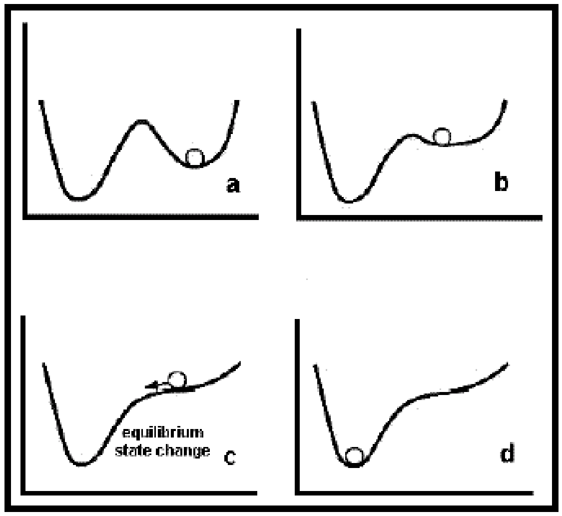

Figure 5. Equilibrium diagrams. (Adapted from Holling, et al. 1995)

COMPLEX SYSTEMS: A POINT OF DEPARTURE

Mechanistic models of single processes are often powerfully explanatory in regard to the behavior of individual system components, but attempts to assemble satisfactorily predictive, unified models from these components have been largely unsuccessful (Ulanowicz 1997). The ability to predict whole system behavior from mechanistic models fails because it is impossible to anticipate and account for the effects of every subtle aspect of system behavior. Current ecosystem and disturbance models are constructed in an explicit manner, defining exactly how modules and equations and variables react and interact. The whole system in its infinite detail is not the right referent; the focus should be on prediction with regard to phenomena (Allen and Hoekstra 1993).

The questions asked of ecological systems often generate middle number models (O'Neill, et al. 1986). Attempts to seek mechanistic causes for overall system behavior through the approaches favored by traditional hard science cannot yield explanations and quantitative answers that are definitive when a middle number system is invoked. Funtowicz and Ravetz (1994) have noted that cause and effect explanations have limited power because in complex systems these categorical distinctions disappear. Ecological systems invite casting them as complex, and complex systems require different causal models. A complex systems approach incorporates the explanatory power of positive and negative feedbacks and the recognition of the emergence of hierarchically self-organizing and self sustaining structures to characterize system behavior (Holling, et al. 1996). Because complex systems do not permit the definitive answers of traditional hard science approaches, a methodology of complex systems is needed to provide soft answers with good explanatory power.

Disturbance regime and landscape equilibrium are powerful concepts in understanding community and ecosystem development through time. Quantifying regime or equilibrium require that space, time, or both be fixed so that the concepts are scale dependant (O'Neill, et al. 1986). There is also the assumption that climate and vegetative composition do not change significantly. Regimes are typically presented as averages for a landscape when they actually come from multiple disturbances of varying severity, size and season. Regime-based models are very instructive in the analysis of historic landscapes or gaining insight on potential future patch dynamics. They are not, however, highly informative for current forest management and planning, because the forested landscapes and vegetative communities from which the regimes derive no longer exist (and probably will never again), the spatial presence of species on the landscape has changed, new species have been introduced, native species have been greatly reduced or eliminated, climate has changed or is currently changing, humans have greatly increased ignition sources, and human intervention (suppression) alters final fire size and shape. Fire regime needs to be predicted from a model, not be an element within a model (Li and Apps 1996).

ANN models address these concerns. The non-linear response nature of ANN architecture facilitates learning and generalization on a wide range of input and output values (Haykin 1994). An ANN can accept categorical data as well as continuous. Assumptions about the distribution and independence of the input data are not as vital to constructing an effective network as they are to more conventional statistical analyses (Sui 1994). The changing spatial and temporal scales of fire environment variables used in modeling wildfire in the Lakes States present the modeler with all the problems inherent in middle number systems. Employing ANNs allows modeling the meso-scale fire environment in a highly powerful and predictive manner. Even though on the face of it the system appears middle number, the ANN explores system structure until, at an appropriate level of analysis, prediction becomes possible. The ANN recasts the parts of the question so that behavior becomes reliable. It filters out middle number specifications by elimination of pathways that do not provide repetitive behavior.

Fuel Models

Rothermel's original equations assume that the fire is burning through a uniform fuel, across a flat terrain, and with no wind. These simplifying assumptions made the original specification of fire behavior equations possible. Mechanistic fire models based on Rothermel's equations inherited those simplifying assumptions. Fire behavior research over the past 30 years has dealt primarily with how to translate the relationships found in the simple fire environment of a test laboratory to the very complex fire environment found in the outside world.

We need to accept that the highly controlled conditions found in a fire behavior laboratory are rarely if ever found in human managed ecosystems. The landscapes that humans manage fire on have highly complex fuel associations, variable terrain, and unpredictable weather conditions. A new theory of meso-scale fire modeling must start with the foundational assumption that the fire environment is complex and varied. Predictions in fire environments beyond Rothermel's fine-scale equations are accomplished by adding modifying parameters to the original equations. This *elaboration of structure* is considered mere complication by Allen, et al. (1999). The proposition here is an *elaboration of organization* when assessing real fire environments. Our hierarchical complexification, as distinguished from complication by Allen, et al. (1999), in the analysis of fire accepts and incorporates the differing spatio-temporal resolution of the fire environment variables. Input data can be maintained within a GIS as close as possible to original scale and resolution, and ANNs can be used to learn the cross-scale relationships between those fire environment data. What it all comes down to is we collect very fine-grained field data on fuel composition, and then dilute the precision of those data by lumping them into fire behavior fuel models that fit known equations. The lumping hides switching constraints inside the aggregates, generating middle number effects. ANNs preserve the original data resolution and develop a complex, continuous function to describe the fuel landscape.

It is ironic that the decades-long effort to produce a spatially-explicit model that accurately predicts fire behavior has pushed input data requirements beyond that which the typical end user is able to provide. Fuels vary continuously across the landscape, but current concepts of fuel models require human judgement to assign fuels to discrete categories. Each evaluation becomes a separate constraint on the model. What is needed is a new theory of fuel models to inform a complex systems methodology that integrates the three elements of the fire environment triangle into a robust, continuous description of fire fuel.

Since one cannot directly measure fire behavior fuel models (FBFMs) in the field, Keane et al. (1999) hypothesized that FBFMs could be related to the biophysical environment, species composition, and stand structure. Results show that while one can accurately map the biophysical, species and stand properties, the relationship between these elements and FBFMs is not well known and thus the derived fuel model layers had low accuracy. A knowledgeable and experienced team achieved only a 50-70% accuracy rate in developing FARSITE input layers on 1.5 million acres of the Gila Nation Forest (Keane, et al. 1999).

Results from the Gila National Forest mapping effort indicate that a different approach to describing fuel on the landscape is necessary. Fire environment variables should be mapped at a resolution appropriate for the variable in question and kept as close as possible to that original scale. FBFM categorization, via multi-step classification and aggregation procedures, dilutes the precision of the original data. Fuel landscapes are composed of more than the vegetation on them; that vegetation also has a history associated with it (Havlicek 1999). FBFMs can be modified to incorporate short-term weather, but climatic factors vary during the entire lifetime of the vegetation, subtly (or not so subtly) influencing fuel loading. The cross-scale interactions between landscape and climatic processes need to be directly addressed in any model of fire fuels.

As discussed earlier, artificial neural networks are very appropriate for use in analyzing data where the relationship between the inputs and outputs is not well-known. How the fuel landscape was influenced by climate during its early years of development versus its middle or later years is not easily quantified, but can be inferred from weather records, past and present vegetative spectral response, landscape position, timing and type of non-stand replacing disturbances (harvesting, disease, pests, residential development), and inventories of current field conditions (e.g., the three aspects mapped with reasonable accuracy on the Gila National Forest). Using an ANN, spectral data from Landsat TM or other remote sensing platform (historic and current imagery) could be input directly, along with field based mapping of other fire environment variables.

Raw digital numbers from unclassified satellite imagery are the closest we can come to a continuous valuation of landscape fuels, and various sensors integrate spectral response over different spatial and temporal scales. When sub-five meter imagery and radar data become readily available, spectral characterization of fuel landscapes would be possible over almost the entire range of human fire management interests, allowing the development of a consistent, hierarchically-organized, multi-scale fuel model developed for the continent but scalable to regional and local considerations.

To further establish the context in which the fuel landscape developed, additional model input layers may include: surficial geology or soil texture; Landtype Association (LTA) (Jordan, et al. 1996); precipitation (day, week, month and yearly totals); hydrography; elevation, slope and aspect; time since last fire/disturbance; land use/ownership; fire suppression regime; road density; and human population/housing density. Some or all of these elements may be important context for or constraints on fire spread. This floating scale approach to fire and fuel modeling has implications for local, regional and state forest planning, and also can be useful in rapid assessments of fire risk, pointing to areas requiring more finely-scaled analyses.

CONCLUSION

Over the last decade, C. S. Holling developed and refined (Holling 1986; Holling 1992; Peterson, Allen and Holling 1998) a four-box model describing how ecosystems function (Figure 6). The first two boxes refer to the classic ecosystem life cycle stages, from colonization after a disturbance (Box 1: exploitation) through succession proceeding toward climax (Box 2: conservation). This cycling of vegetation from disturbance to climatic/edaphic climax and back to disturbance was the traditional view of ecosystem succession in the first half of the 20th century (Clements 1936). Studies from various researchers in the early 1980's have served to shift our understanding of succession to a more dynamic process (Holling 1992).

Holling (1992) makes four points: 1) following disturbance and during succession, invasion by persistent species can be highly variable and dependant on many random factors; 2) early and late successional species can and will maintain a presence on the landscape through time; 3) disturbance events of varying sizes are part of the ecosystem and affect the timing of succession; and 4) there are multiple potential climax types

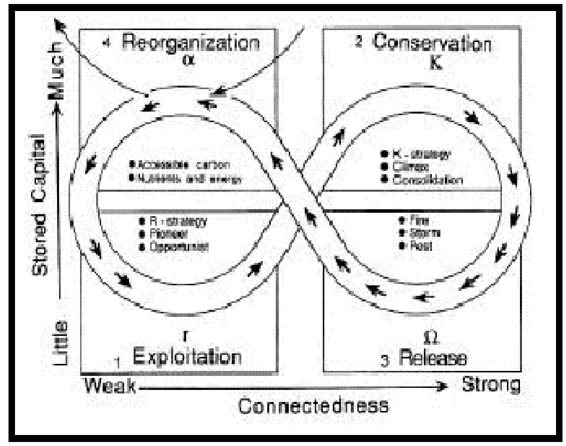

Figure 6. Holling's figure-8 model of ecosystem change.

(stable attractors), and some disturbances can move an ecosystem between attractors (Kay 1993). Recognizing that there is not a unique successional pathway for a given landscape prompted Holling (Holling 1986) to add two additional elements to the model, release or creative destruction (Box 3) and reorganization (Box 4).

The release and reorganization phases of the model have the greatest influence on what successional pathways will recur in the system after disturbance. The accumulation of a large amount of stored capital (e.g., biomass) and organization (e.g., structure and feedback) in the conservation phase eventually leaves the system overconnected (Allen and Starr 1982) and susceptible to some agent of change (e.g., fire). The shift from conservation to reorganization is rapid. The post-disturbance, weakly connected system is now free to exploit the released capital and begin the exploitation phase again. If there is sufficient capital (e.g., organic matter, nutrients) and information (e.g., seed source) left in the system and its surroundings following disturbance, succession may return to its predisturbance trajectory (O'Neill, et al. 1986). If the disturbance is great in extent or severity (i.e., most of the capital or information is lost) the system can change qualitatively from one successional pathway (attractor) to another (Ulanowicz 1997). The arrows into and out of Box 4 signify the possibility for change in ecosystem processes, an escape to another basin of attraction where a qualitatively different four-box model describes the system.

The four-box model of birth, growth, death and renewal processes spans many scales. The figure-8 describing processes within a single forest stand has smaller figure-8's nested within it (e.g., individual tree birth, growth, death and decomposition) while the stand figure-8 is nested within a larger, regional scale four-box model. The S-curve dynamics and multiple disturbance types, incorporated into the four-box ecosystem model, would show that disturbances can act serially to effect a change greater than would have occurred if each disturbance was modeled independently.

Holling (1986, 1995) presents different viewpoints that aid in understanding whence come societal perceptions of ecology and how these relate to management. An equilibrium-centered view assumes nature is constant or only changes slowly so human knowledge and technology can keep up - resources are never limited (Nature Cornicopian) because we invent substitutes. A second view is that of dynamic, Nature Resilient, with multiple stable states, variability, heterogeneity and instability - it accepts that complete knowledge of the system is\ unattainable and management must allow variation and maintain resilient structures in the process of extracting benefits. From this viewpoint we can chart a course of societal change and management that transitions to a sustainable human presence. Alternatively, Holling's four-box model focuses more on Nature Resilient with nested cycles of order and collapse, renewal and innovation. A final, emerging viewpoint, Nature Evolving, comes out of the more recent sciences of chaos, complex systems analysis, self-organizing systems, nonlinear behavior and discontinuous change.

From analyses of historical management practices and modifying Holling's four-box model, Gunderson, et al. (1995) present a general model of ecosystem management. A cycle of four phases is described: 1) exploitation (management to facilitate progress); 2) canalization (management is static, while ecosystem changes with society); 3) crisis (environmental surprises and social conflicts arise); and 4) reorganization (management learns and adapts to new configuration). The Nature Evolving viewpoint seeks interdisciplinary, adaptive institutions that understand that constraining natural variability reduces the resilience of ecosystems (Holling 1995).

The history of fire management in the U. S. has experienced several of these cycles on a local and national basis. With global climate change, El Nino events, and six billion people demanding resources from our forested lands, fire's role as a management tool is probably approaching crisis. The inevitable reorganization phase will need adaptive models. We anticipate that our approach to wildfire modeling will have significant impact on how we manage fire susceptible lands and human actions on them. With proper design, the model interface will allow fire managers to update the ANN with each new fire, allowing the model to change incrementally with time (hopefully tracking fire regime changes in real time). The influence of short-term (days or weeks) and long-term (years or decades) climate, vital environmental constraints, could be assessed and directly incorporated into the ANN. These evolutionary abilities of the model will prove useful in light of the uncertainties of global climate change. Furthermore, by decomposing the ANN weights we hope to find the environmental factor thresholds that, once crossed, allow fires to escape suppression and control efforts. An ANN-based modeling approach will determine what factors control fire on a given LTA, watershed or forest, and whether those factors are the same or different on each landform analyzed.

Recognition and characterization of the emergent properties of wildfire (Green 1993b) with changing controlling factors are vital to developing long-term ecosystem management strategies. By not incorporating these concepts managers will continue to be surprised by, and unprepared for, catastrophic wildfire events.

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